

DOI: <http://10.32441/kjps.02.02.p3>

An Enhancement of Simultaneous Localization and Mapping Model Using Artificial Neural Networks

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ABSTRACT

This paper presents a model of Environment Representation Architecture for Intelligent Robot. The model consists of a vehicle, an environment, and landmarks. The proposed method is based on using SLAM based on ANN, back propagation algorithm, to be trained on predefined datasets on some environment. In this paper we used Using Artificial Neural on the Simultaneous Localization and Mapping enhances the obtained maps of the robot. Limitation of this paper to test the proposed system, different maps with different datasets are required, however, these datasets, need expensive sensors, vehicles and GPS receivers to be built. Use this information to build their decisions. The systematic error was solved by the proposed approach using ANN, depends only on the initial values that were used during the training phase, it considers previous landmarks in order to build the next route, but on the other hand, it does not accumulate the previous error.

Keywords: Simultaneous Localization and Mapping (SLAM), Artificial Neural Network (ANN).

تعزير خوارزمية التوطين ورسم الخرائط في ان واحد باستخدام الشبكات

العصبية الاصطناعية

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الملخص

يقدم هذا البحث نموذج لهيكلية تمثيل البيئة للروبوت الذكي باستخدام الشبكات العصبية الاصطناعية. النموذج يتكون من سيارة، بيئة ومعالم. الطريقة المقترحة هي مبنية على استخدام التوطين ورسم الخرائط في وقت واحد بالاعتماد على الشبكات العصبونية الذكية، خوارزمية الانتشار الخلفي، ليتم تعليمها على مجموعات البيانات المعرفة مسبقاً لنفس البيئة. في هذا البحث تم استخدام الشبكات العصبونية الذكية والتوطين ورسم الخرائط في وقت واحد لتطوير الخريطة المبنية للبيئة عن طريق الروبوت. المحددات في هذا البحث تكمن في فحص النظام المقترح. خرائط مختلفة مع مجموعات بيانات مختلفة مطلوبة، هذه المجموعات من البيانات تحتاج مجسات عالية الثمن مركبة وأجهزة استقبال واحداثيات ليتم بناؤها. تم حل الخطأ المنهجي من خلال النهج المقترح باستخدام الشبكات العصبية الاصطناعية، بالاعتماد فقط على القيم الأولية التي استخدمت خلال مرحلة التدريب، بالنظر للمعالم السابقة من أجل بناء الطريق التالي، لتجنب عدم تراكم الاخطاء السابقة.

الكلمات الدالة: خوارزمية التوطين ورسم الخرائط في ان واحد، الشبكات العصبية الاصطناعية.

1. Introduction

Many natural systems of most creatures in the world are very rich topics for the scientific researchers, since that a simple individual behavior can cooperate to create a system able to solve a real complex problem and perform very sophisticated tasks [1] "SLAM has been performed theoretically in different forms; it is also implemented in different domains, such as, indoor, outdoor and underwater environments. Probabilistic SLAM problem was first proposed at the IEEE Robotics and Automation Conference on 1986. Many researchers had been working on applying estimation-theoretic methods to environment mapping and

localization problems. A few years later a new statistical method was established by Smith, Cheesman and Durrant-White" [2]. "This statistical based for measuring the relationships between landmarks in addition to manipulating geometric uncertainty. They showed in their work that there must be a high degree of correlation between the estimation of different landmark locations in the map, which grows with successive observations".

Zhan et al [3], "focused on visual methods to find solutions to this problem, using sensor fusion navigation, resulted in enhancing the landmark representation of the environment, other researches based on visual methods allowed a mobile robot to move through an unknown environment taking relative observations of landmarks" [4] [5]. "The high correlation between the estimates of these landmarks was due to the margin of error in the estimated vehicle location" [6].

"The landmarks positions in addition to the vehicle situations shape a full solution to the localization and mapping combined problem. However, a huge state vector required to be implemented scaling the number of landmarks in the map. Thus, the researchers considered the complexity of the mapping problem computations only, regardless of its convergence, they focused their attention on a sequence of approximations to the solution of the localization and mapping problem. Their method considered minimizing the high correlation between the landmarks, resulted in reducing the usage of the filter to a series of decupled landmark to vehicle filter" [7] [8].

"SLAM problem structure and the results of the convergence was first presented. Recently, several kinds of research and approaches were proposed on the theory of convergence, such as [9] [10] [11]. Also on localization and mapping", such as [12] [13] [14] [15] [16] [17], "working on indoor, outdoor and underwater environments" [18].

Modeling of environment for use in robotic systems has, in fact, become a major focus of contemporary autonomous robotic research. There are many researchers have done research in this area, but are considering the specific environment and this research considering the general environment. There are problems related to the development of a model for general environments, such as; How to build a robotic system capable of building map proximity

form the original environment by identifying the characteristics of the environment and work in any environment. How to identify the relationships between required information for a robot related to an environment with the robot tasks. Simultaneous Localization and Mapping (SLAM) algorithm, is an algorithm used by robots for map building, this work will be based on SLAM algorithm calculations to produce the mapped datasets and landmark. On the other hand, Artificial Neural Network (ANN) algorithms are very important for modern systems, which it can be trained and work without pre-requests. While SLAM requires pre-requests in order to build the robots landmarks and map. The proposed system in this work uses ANN to allow the robots to build its own map without pre-requests. Moreover, ANN enhances SLAM and allows the robot to map any environment.

2. Methodology

The proposed model for the environment representation architecture consists of five parts; these are Organize Object in environment, landmark, localization, algorithm SLAM, and Apply of ANN form the environment, as seen in figure 1.

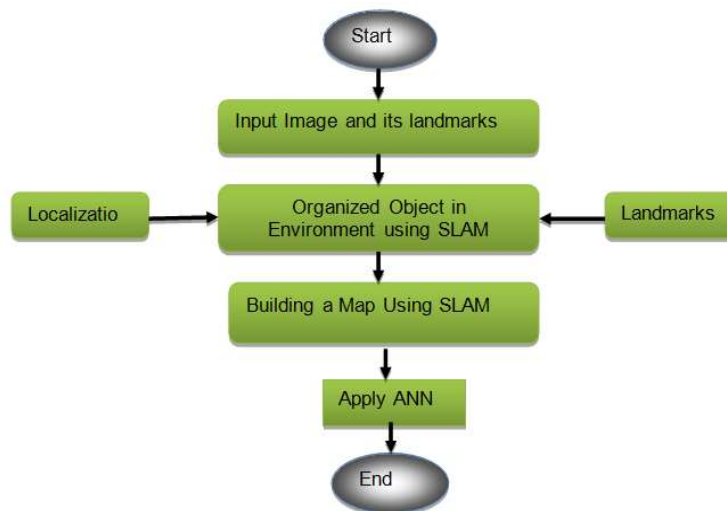


Figure 1: Flow chart of Development Representation an Environment for Robot

2.1 The Environment

In this paper will be considered one types of environment that is static. The static environment is the environment that does not change and can be easily dealt with by an intelligent agent [20].

Using SLAM for construction of a map for the environment for a priori data or put the update on a given map in a known environment using vehicle without forgetting to keep its track of the position [20].

In the following subsections are the brief descriptions for SLAM objectives, building a map and locating the vehicle simultaneously.

SLAM makes a vehicle capable to move in an environment with an unknown location, moreover [21]. It allows the vehicle to map this environment simultaneously, and use this map to calculate vehicle location. Figure 2 presents how to do SLAM using internal representations for the positions of landmarks (map) and the vehicle parameters, always takes the zero starting position.

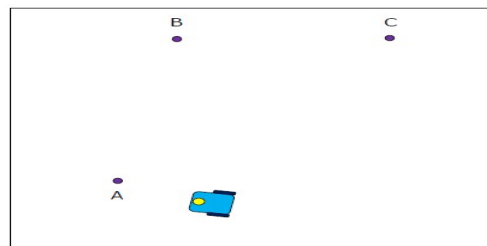


Figure 2: SLAM Behavior [23]

Localization and mapping are coupled, each has a relationship with the other For this reason, been getting better results [23].

2.2 Modeling Vehicle Coordinated System

To position the used vehicle several parameters as shown in Figure 4. "In Figure 4 explain vehicle navigation in the environment, that means the robot's ability to determine the

position in the environment and then to plan a path towards goal location. Navigation can be defined as the combination of the three fundamental competencies: localization, path planning, map-building. Robot localization denotes the robot's ability to determine its position and orientation in the environment. Path planning is effectively an extension of localization, in that it requires the determination of the robot's current position and a position of a goal location. Map building can be in the shape of a metric map or any way. In this study use, steering control alpha is defined in vehicle coordinate frame; the laser sensor is located in the front of the vehicle and returns range and bearing related to objects at distances of up to 50 meters, high-intensity reflection can be obtained by placing high reflectivity beacons in the area of operation".

In this study use "steering control alpha is defined in vehicle coordinate frame as shown in Figure 4; the laser sensor is located in the front of the vehicle and returns range and bearing related to objects at distances of up to 50 meters, high-intensity reflection can be obtained by placing high reflectivity beacons in the area of operation".

"The landmarks are labeled as $B_i (i=1..n)$ and measured with respect to the vehicle coordinates (x_1, y_1) , that is $\mathcal{A}(k) = (r, b, I)$, where r is the distance from the beacon to the laser, b is the sensor bearing measured with respect to the vehicle coordinate frame and I is the intensity information".

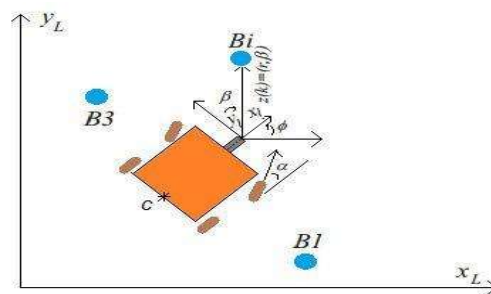


Figure 3: Vehicle Coordinated System

Figure 5 shows the kinematic parameters of the vehicle. This figure does not change (fixed) explains measurements between the landmarks of the environment and the landmarks of the vehicle and between measurements components of the vehicle.

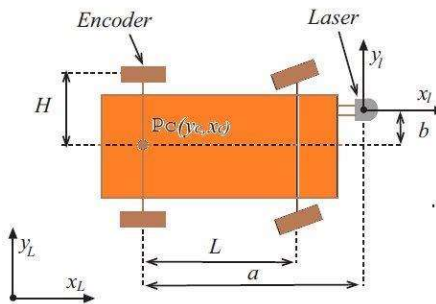


Figure 4 Kinematics parameters

"Suppose that the vehicle is controlled through the vehicle velocity V_c and the steering angle α . Then to predict the trajectory of the back axle center C, the below equation should be followed. Because the laser is located in the front of the vehicle, the translation of the center of the back axle, the transformation data is defined by the orientation angle, the velocity is generated by the encoder and translated to the center of the axle".

2.4 Artificial Neural Networks

A neural network "consists of a set of neurons connected together by weighted connections. It is characterized mainly by the type of units used and by its topology. There are two types of specific neurons in a network: neurons receiving input data from the outside world (the situation) and the output neurons providing the result of the performed treatment (the evaluation)"[26].

2.4.1 Architecture of ANN

Input layer represents the raw information that is fed into the network that consists of 16 layers. This part of the network is never changing its values. Every single input to the network is duplicated and sends down to the nodes in the hidden layer. Hidden Layer accepts data from the input layer. It uses input values and modules them using some weighted value, this new value is then sent to the output layer but it will also be modified by some weight from the connection between hidden and the output layer. Output layer consist of 16 layer process information received from the hidden layer and produces an output [26].

2.5 Back Propagation (BP) Algorithm

One of the most popular NN algorithms is "backpropagation algorithm. Claimed that BP algorithm could be broken down to four main steps. After choosing the weights of the network randomly, the backpropagation algorithm is used to compute the necessary corrections. The basic formula for BP algorithm". "The algorithm can be decomposed in the following four steps"[27]:

- Feed-forward computation.
- Backpropagation to the output layer.
- Backpropagation to the hidden layer.

3. Implementation of the Model to Build Map

The evaluated of this algorithm by using MATLAB® R2013a. The systematic error found in Nebot's work was solved by the proposed approach, because, using ANN, depends only on the initial values that were used during the training phase, it considers previous landmarks in order to build the next route, but it does not accumulate the previous error.

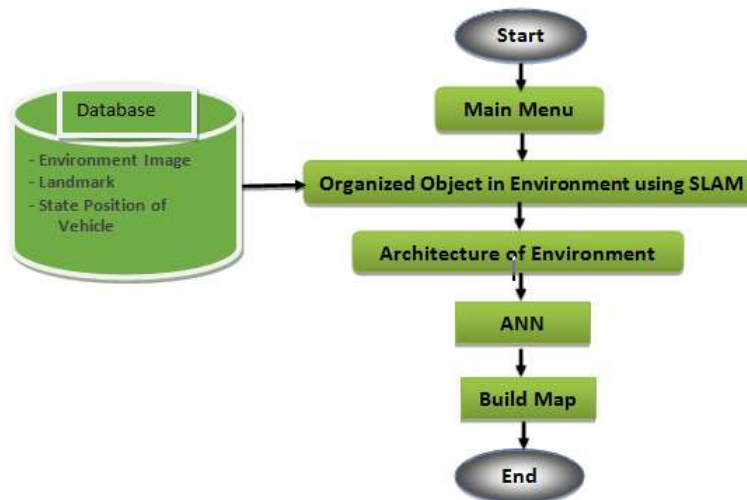


Figure 5: a Flow chart for Implementation the model to build a map

4. Results and Discussion

The navigation system was tested with a utility vehicle retrofitted with the described sensors. The utility car used for the experiment is shown in Figure 9.



Figure 6: Utility car used for the experiments (Nebot 2000)

In the experiment," using the dataset contains the true landmarks and GPS coordinates for his map were taken from Drexel Autonomous System Lab datasets, which were scanned using a SICK scanner (Drexel), in this study used the vehicle model and sensor pose, mentioned earlier". The "stars in the map represent potential natural landmarks and the "circles" are the artificial reflective beacons. Although this environment is very rich with respect to the number of natural landmarks, the data association becomes very difficult since most of the landmarks are very close together". The evaluation of the model was using MATLAB[®] R2013a. After explaining the proposed approach and methodology, in addition to the experiment and evaluation of this approach, in the next section, the result showing for SLAM and ANN as seen in figure 7,8:

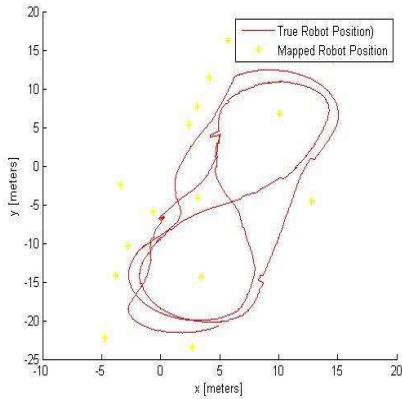


Figure 7: The Result Map from ANN

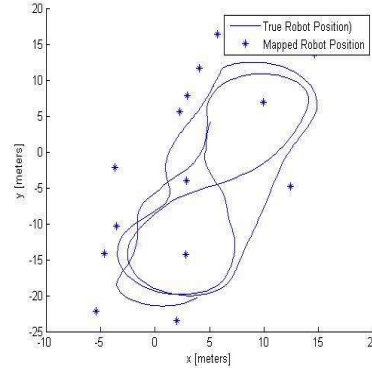


Figure 8: Building Map Using SLAM

To improve results and reduce the error in the artificial neural network by giving you a number of examples of (input) in order to give better results and working principle of this artificial neural network

The resulted map is shown in the below Figure 9.

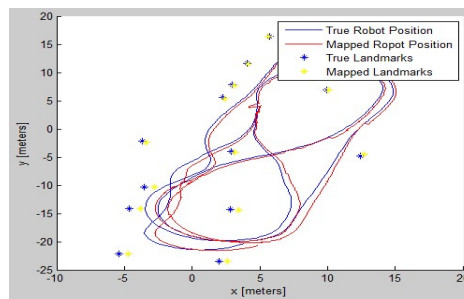


Figure 9: True and Robot Maps

As it is shown in Figure 5 above, you have reached a relatively good result in mapping the landmarks and the environment, the robot followed the same direction, but with small error margin.

The ANN error histogram is shown in the below Figure 10.

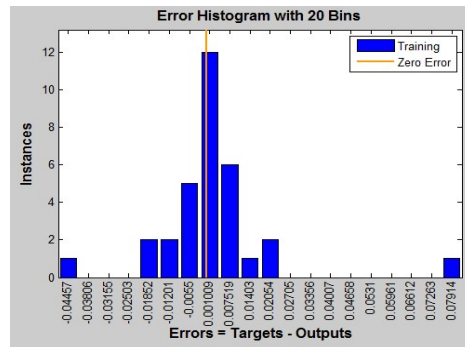


Figure 10: ANN Model Error Histogram

The performance plot is shown in Figure 11, below.

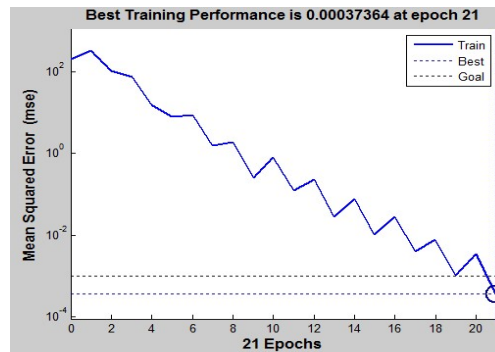


Figure 11: Performance Plot

From the error histogram and the plots above, "it is noticed that good results of landmarks mapping are reached, which is very close to the true landmarks position. Based on that, very good results of environment mapping have been obtained, as shown in Figure 9 above; the model mapped line is very close to the true line".

It can be noticed from the figures above, that very good results in comparison to the previous works are reached, some of them discussed previously. Using Artificial Neural Network (ANN) enhanced the accuracy of the map, which is noticed in figure 8 where the mapped landmarks and routes are almost the same. Moreover, using ANN enhanced the speed of

map building which is a very important achievement especially in real-time applications, or in robots that use this information to build their decisions.

The systematic error found in Nebot's work (Nebot 2000), "was solved by the proposed approach, because, using ANN, depends only on the initial values that were used during the training phase, it considers previous landmarks in order to build the next route, but on the other hand, it does not accumulate the previous error. The table show of the compression between the work of SLAM and ANN".

4.1 The Developed Application

In this section, work is enhanced SLAM algorithm based on ANN. In this method, using Back-propagation ANN to make the robot estimate the locations of landmarks accurately.

In this algorithm "used the equations of the SLAM landmark equations to train a neural network; a landmark dataset is also used from Drexel Autonomous System Lab datasets, which were scanned using a SICK scanner (Drexel)" as seen below:

The original landmark \longrightarrow SLAM algorithm \longrightarrow result of SLAM (build map using
(Input) SLAM)

In this works has been trained the ANN on the SLAM landmark equation results as seen below:

The result of SLAM \longrightarrow operation ANN \longrightarrow result of ANN (build map using ANN)
(Input)

The evaluated of this algorithm by using MATLAB® R2013a. The systematic error found in Nebot's work was solved by the proposed approach, because, using ANN, depends only on the initial values that were used during the training phase, it considers previous landmarks in order to build the next route, but it does not accumulate the previous error.

5. Conclusions

The proposed solution for this book concerns the localization of a vehicle and an environmental mapping simultaneously. The design of this algorithm, in addition to the modeling aspects, is presented with an implementation of it. Modeling SLAM using landmarks does not require any landmarks surveying.

References

- [1]. Hussein H. Owaied, Suhaib I Al-Ghazi, *"Developing Cognitive Map from Blueprint Map"*, Trent of Applied Sciences Research, Issue 6, No. 8, pp 848-862 (2011).
- [2]. H.F. Durrant-Whyte. *"Uncertain geometry in robotics"*. *IEEE Trans. Robotics and Automation*, 4(1):23-31, (1988).
- [3]. Zhang, Xinzheng, Ahmad B. Rad, and Yiu-Kwong Wong. *"Sensor fusion of monocular cameras and laser rangefinders for line-based simultaneous localization and mapping (SLAM) tasks in autonomous mobile robots."* *Sensors* 12.1, 429-452 (2012).
- [4]. Engelhard, Nikolas, et al. *"Real-time 3D visual SLAM with a hand-held RGB-D camera."* Proc. of the RGB-D Workshop on 3D Perception in Robotics at the European Robotics Forum, Vasteras, Sweden. Vol. 2011. 2011.
- [5]. Gil, Arturo, et al. *"A comparative evaluation of interest point detectors and local descriptors for visual SLAM"*, *Machine Vision and Applications* 21.6 (2010): 905-920.
- [6]. J.J. Leonard and H.F. Durrant-Whyte. *"Simultaneous map building and localization for an autonomous mobile robot"*. In Proc. IEEE Int. Workshop on Intelligent Robots and Systems (IROS), pages 1442-1447, Osaka, Japan, 1991.
- [7]. Sola, Joan, et al. *"Impact of landmark parametrization on monocular EKF-SLAM with points and lines."* *International journal of computer vision* 97.3 (2012): 339-368.
- [8]. Carrillo, Henry, Ian Reid, and José A. Castellanos. *"On the comparison of uncertainty criteria for active SLAM"*, *Robotics and Automation (ICRA), 2012 IEEE International Conference on*. IEEE, 2012.



- [9]. H. Durrant-Whyte, D. Rye, and E. Nebot. *"Localisation of automatic guided vehicles"*. In G. Giralt and G. Hirzinger, editors, Robotics Research: The 7th International Symposium (ISRR'95), pages 613-625. Springer Verlag, 1996.
- [10]. Cheein, Fernando A. Aunt, and Ricardo Carelli. *"Analysis of different feature selection criteria based on a covariance convergence perspective for a SLAM algorithm"* Sensors (Basel, Switzerland) 11.1 (2011): 62.
- [11]. Dissanayake, Gamini, et al. *"Convergence comparison of least squares based bearing-only SLAM algorithms using different landmark parametrizations."* (2012).
- [12]. Benini, A., et al. *"Adaptive extended Kalman filter for indoor/outdoor localization using an 802.15. 4a wireless network."* Proceedings of the 5th European Conference on Mobile Robots ECMR. 2011.
- [13]. Kümmerle, Rainer, et al. *"Large scale graph-based SLAM using aerial images as prior information"*, Autonomous Robots 30.1 (2011): 25-39.
- [14]. McDonald, John, et al. *"6-DOF multi-session visual SLAM using anchor nodes"*, European Conference on Mobile Robotics, Orbero, Sweden. Vol. 13. 2011.
- [15]. Lee, Yong-Ju, Jae-Bok Song, and Ji-Hoon Choi. *"Performance Improvement of Iterative Closest Point-Based Outdoor SLAM by Rotation Invariant Descriptors of Salient Regions"*, Journal of Intelligent & Robotic Systems (2012): 1-12.
- [16]. Mei, Christopher, et al. *"Hidden view synthesis using real-time visual SLAM for simplifying video surveillance analysis"*, Robotics and Automation (ICRA), 2011 IEEE International Conference on. IEEE, 2011.
- [17]. Stachniss, Cyrill, Stefan Williams, and José Neira. *"Editorial: Visual navigation and mapping outdoors"*, Journal of Field Robotics 27.5 (2010): 509-510.
- [18]. Lee, Yong-Ju, Joong-Tae Park, and Jae-Bok Song. *"Three-dimensional outdoor SLAM Using rotation invariant descriptors of salient regions"*, Control, Automation and Systems (ICCAS), 2011 11th International Conference on. IEEE, 2011.
- [19]. M.W.M.G. Dissanayake, P.Newman, H.F. Durrant-Whyte, S. Clark, and M.Csobra. *"An experimental and theoretical investigation into simultaneous localization and map building (SLAM)"*. In Proc. 6th International Symposium on Experimental Robotics, Pages 171-180, Sydney, Australia, March 1999.



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- [20]. Berns, Karsten, and Ewald von Puttkamer. *"Simultaneous localization and mapping (SLAM)"*, Autonomous Land Vehicles. Vieweg+ Teubner, 2009. 146-172.
- [21]. Chin, Wei Hong, and Chu Kiong Loo. *"Topological Gaussian ARAM for Simultaneous Localization and Mapping (SLAM)"*, Micro-NanoMechatronics and Human Science (MHS), 2012 International Symposium on. IEEE, 2012.
- [22]. Margarita Chli, *"Simultaneous Localization And Mapping"*, AUTONOMOUS SYSTEMS LAB, (2011).
- [23]. Drexel Autonomous System Lab (DASL). *"Simultaneous Localization and Mapping (SLAM)"*, Drexel University (2011).
- [24]. Nebot Eduardo, Jose Guivant and Stephan Baiker " *Autonomous Navigation and Map building Using Laser Range Sensors in Outdoor Applications*", Journal of robotics systems, Vol 17, No 10, October, (2000).
- [25]. Mirza Cilimkovic, " *Neural Networks and Back Propagation Algorithm, Institute of Technology*", (2009)
- [26]. Raul Rojas, *"Neural Networks: A Systematic Introduction"*, (2005).